Expert Systems with Applications 37 (2010) 4999–5008

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A new TOPSIS-based multi-criteria approach to personnel selection

Alecos Kelemenis *, Dimitrios Askounis

National Technical University of Athens, Greece

ARTICLE INFO

Keywords:
Personnel selection
Multi-criteria decision making
Fuzzy TOPSIS
Veto threshold

ABSTRACT

Selection of qualified human resources is a key success factor for an organization. The complexity and importance of the problem call for analytical methods rather than intuitive decisions. The aim of this paper is to support adequately the decision making process. The steps of fuzzy Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) are considered, incorporating a new concept for the ranking of the alternatives. This is based on the veto threshold, a critical characteristic of the main outranking methods. The ultimate decision criterion is not the similarity to the ideal solution but the distance of the alternatives from the veto set by the decision makers. Additionally, a real life application on the selection of a top management team member shows the practical implications.

1. Introduction

It is a common belief that IT comprises a crucial factor for the development and growth of an organization. Nevertheless, in practice, the IT function acts often as a support role in business rather than as a leader and strategic partner (Ward & Peppard, 1996). This is true considering that scarcity makes a resource truly strategic, while IT resources have become available and affordable to all (Carr, 2003). Studies recognize that many components of IT infrastructure (such as off-the-shelf computer hardware and software) convey no particular strategic benefit due to lack of rarity, ease of imitation, and ready mobility (Wade & Hulland, 2004). What cannot be imitated are the managerial IT skills, in comparison to other IT resources. The study of Mata, Fuerst, and Barney (1995) empirically supported the link between managerial IT skills and firm performance. Powell and Dent-Micallef (1997) divided IT resources into three categories: human resources, business resources, and technology resources. In a study of the US retail industry, they found that only human resources in concert with IT contributed to improved performance. Firms with strong human IT resources are able to (a) build internal relationships between the Information Systems (IS) function and other departments of the firm, leading to integrated planning processes at corporate level, (b) manage relationships between the IS function and stakeholders outside the firm, (c) anticipate future business needs of the firm and innovate valuable new product features before competitors and in parallel manage effectively the resulting technology change and growth (Bharadwaj, 2000; Bharadwaj, Sambamurthy, & Zmud, 1998; Mata et al., 1995).

Literature on IT management has reported more cases of failed implementations than of success (Dhillon, 2008). Many communication and leadership inadequacies have been identified amongst senior IT managers and consequent breakdowns in the IT/business relationship (Willcoxson & Chatham, 2006). As Enns, Huff, and Golden (2003) demonstrated, Chief Information Officers (CIOs) usually lack the interpersonal and conceptual skills needed to influence others in the organization. For instance, CIOs spend much of their time attempting to convince other top managers to commit to strategic IT initiatives (Lederer & Mendelow, 1988), share in a vision for IT (Earl & Feeny, 1994), and allocate resources to IT projects (McKenney, Mason, & Copeland, 1997). Many IS/IT professionals speak in jargon that shows a basic ignorance of the rest of the world of organizational leaders (Service, 2005). Taking into account the above mentioned and the fact that technical qualifications should be considered as precondition, the critical dimensions of human IT resources include: (a) technical IT skills, such as programming, systems analysis and design, and competencies in emerging technologies, and (b) the "soft" IT skills, which include abilities such as information management skills, communication and negotiation skills, process and project management and leadership skills (Bharadwaj, 2000; Ward, 1999).

Selection of IT professionals is then a critical factor for successful IT management. In general, personnel selection, depending on the firm's specific targets, the availability of means and the individual preferences of the decision makers (DMs), is a highly complex problem. The multi-criteria nature of the problem makes Multi-Criteria Decision Making (MCDM) methods and fuzzy logic ideal to cope with this, given that they consider many criteria at the same time, with various weights and thresholds, having the

* Corresponding author. Address: National Technical University of Athens, School of Electrical and Computer Engineering, 9, Iroon Polytechniou str., Zografou 15773, Athens, Greece. Tel.: +30 210 7723612/3583; fax: +30 210 7723550.
E-mail address: akel@epu.ntua.gr (A. Kelemenis).
URL: http://www.epu.ntua.gr/ (A. Kelemenis).

0957-4174/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2009.12.013

potential to reflect at a very satisfactory degree the vague – most of the times – preferences of the DMs.

The rest of the paper is organized as follows: In the next section, the main MCDM methods are summarized while some relevant studies on the personnel selection problem are presented. In Section 3, the principles of the fuzzy sets are demonstrated in brief. Section 4 presents the proposed approach to support the decision making. Section 5 briefly presents an empirical application of the proposed approach for the selection of a senior IT officer. Finally, future steps and research challenges are discussed.

2. Multi-criteria decision making methods

In most of the situations where a decision must be taken, it is rare for the DM to have in mind a single clear criterion (Figueira, Greco, & Ehrgott, 2005). Such situations, where a single-criterion approach falls short, refer to as MCDM problems.

Many terminologies have been proposed for the categorization of MCDM problems. The dominant terms are the one of Multi-Criteria Decision Analysis (MCDA) or Multi-Attribute Decision Making (MADM), for problems in which the DM must choose from a finite number of explicitly available alternatives characterized by a set of multiple attributes (or criteria) and the one of Multi-Objective Mathematical Programming (MOMP) or Multi-Objective Decision Making (MODM) that deal with decision problems characterized by multiple and conflicting objective functions that are to be optimized over a feasible set of decisions. Here, the alternatives are not explicitly known a priori (Figueira et al., 2005). In what follows, the main categories of MCDM are presented.

2.1. Multi-criteria decision analysis

The aim in MCDA is to determine overall preferences among alternative options. In this context, the decision is facilitated by evaluating each option based on a set of criteria. The criteria must be measurable and their outcomes must be measured for every decision option. Criterion outcomes provide the basis for comparison of option and consequently facilitate the final decision of choice, sorting or ranking, depending on the specificities of the decision problem. The MCDA methods can be divided into two main categories; the outranking methods (Roy, 1993) and the multi-attribute utility and value theories.

2.1.1. Outranking methods

Outranking methods are based on pairwise comparison of actions. Outranking indicates the degree of dominance of one alternative over another. The alternative *a* is deemed better than alternative *b* if the number of criteria indicating that alternative *a* is better than alternative *b* is larger than the number of criteria indicating the opposite. The usual case is the one of ranking the alternatives. The most commonly used outranking methods for ranking problems are PROMETHE II and ELECTRE III. In these, criteria are treated as so-called pseudo-criteria. This means that a threshold model is applied to the original criteria value. If the criteria values are sufficiently close to each other, they are indifferent to the DM (indifference threshold) and if the difference between the criteria values is sufficiently large, there is no doubt which alternative is better according to that criterion (preference threshold) (Figueira et al., 2005). In between, there is an area, in which the DM is assumed to hesitate between indifference and strict preference. In addition, these methods can be considered as non-compensatory models, meaning that a really bad score of any alternative with respect to any one criterion cannot necessarily be compensated for by good scores in other criteria. Thus, the alternative with a very poor value of any one criterion cannot be chosen irrespectively of the values of the other criteria (Kangas, Kangas, & Pykäläinen, 2001).

2.1.2. Multi-attribute utility and value theories

The multi-attribute utility theory (MAUT) tries to assign an overall utility value to each alternative. This utility is a real number representing the preferability of the considered alternative. Weights that reflect the relative importance of the attributes are defined. These weights are typically scaled so that they sum to unity. For each alternative a marginal utility value is assigned to each attribute and the sum of the products of attribute marginal utility and attribute importance is calculated. This weighted sum represents the overall utility value associated with the alternative. The optimal alternative is the one with the higher overall utility value (Figueira et al., 2005).

The UTA (Utilités Additives) method was proposed by Jacquet-Lagreze and Siskos (1982). The UTA method refers to the philosophy of assessing a set of value or utility functions, assuming the axiomatic basis of MAUT and adopting the preference disaggregation principle. UTA methodology uses linear programming techniques in order to optimally infer additive value/utility functions, so that these functions are as consistent as possible with the global DM's preferences (inference principle). The behaviour and the cognitive style of the DM are analyzed; special iterative interactive procedures are used, where the components of the problem and the DM's global judgment policy are analyzed and then they are aggregated into a value system.

The analytic hierarchy process (AHP), developed at the Wharton School of Business by Saaty (1980), allows the DMs to model a complex problem in a hierarchical structure showing the relationships of the goal, objectives (criteria), sub-objectives, and alternatives. AHP is based on three basic principles: decomposition, comparative judgments, and hierarchic composition or synthesis of priorities (Saaty, 1990). Decomposition principle is applied to structure a complex problem into a hierarchy of clusters, sub-clusters, sub-sub-clusters and so on. The principle of comparative judgments is applied to construct pairwise comparisons of all combinations of elements in a cluster with respect to the parent of the cluster. These pairwise comparisons are used to derive "local" priorities of the elements in a cluster with respect to their parent. The principle of hierarchic composition or synthesis is applied to multiply the local priorities of elements in a cluster by the "global" priority of the parent element, producing global priorities throughout the hierarchy and then adding the global priorities for the lowest level elements (the alternatives). Two of the main characteristics of this method are that it enables DMs to derive ratio scale priorities or weights as opposed to arbitrarily assigning them and that it is a compensatory decision methodology because alternatives that are deficient with respect to one or more objectives can compensate by their performance with respect to other objectives (Forman & Selly, 2001).

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was firstly proposed by Hwang and Yoon (1981). The approach is based on a synthesizing criterion like MAUT and AHP. The main concept of this method is that the most preferred alternative should have the shortest distance from the positive ideal solution (PIS) and the longest distance from the negative ideal solution (NIS). PIS is the one that maximizes the benefit criteria and minimizes the cost criteria, while the NIS maximizes the cost criteria and minimizes the benefit criteria (Wang & Elhag, 2006). In traditional TOPSIS, the weights of the criteria and the ratings of alternatives are known precisely and are treated as crisp numerical data. However, under many conditions crisp data are inadequate to model real-life decision problems; in addition, perfect knowledge is not easily acquired. Unquantifiable, incomplete and non-obtainable information (Ölçer & Odabaşi, 2005) make precise